

Decentralized demand side management of plug-in hybrid vehicles in a Smart Grid

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ABSTRACT

Research predicts that in 2030, around 30% of all vehicles in Belgium will be plug-in hybrid electric vehicles (PHEVs). Because most PHEVs are charged after working hours, the existing peak load in the evening will increase significantly. Large peak loads cause more expensive production and can even damage the electricity infrastructure.

In a Smart Grid, the charging of PHEVs can be controlled to reduce peak load, denoted as demand side management (DSM). The goal of our research is to compare several solutions for DSM of PHEVs. This paper takes a first step by benchmarking a multi-agent solution against an optimal quadratic programming (QP) scheduler solution.

Simulations show that a QP scheduler is able to optimally flatten peak loads while sufficiently charging the PHEV batteries. However, this solution is unfeasible in practice because it scales poorly and requires complete information on when and how much PHEVs need to charge beforehand, which is not available. The MAS solution proves to be scalable and adaptable to incomplete and unpredictable information while peaks are still reduced with an efficiency up to 95% compared to the QP scheduler.

Categories and Subject Descriptors

H.4 [Information Systems Applications]: Miscellaneous

General Terms

Algorithms, performance, experimentation

Keywords

Plug-in hybrid vehicles, multi-agent system, electricity infrastructure, electrical power systems automation.

1. INTRODUCTION

In 2009, road traffic has been responsible for 12.3 percent of the global emission of greenhouse gasses [1]. Together with rising fuel prices, awareness grows that electrical cars are necessary for a more economical and environmental friendly road traffic. The first step towards the electrification of the car is a plug-in hybrid electrical vehicle (PHEV). A PHEV has both an electrical and a combustion engine together with a battery that can be charged through a plug. The advantage of a PHEV is that short drives can be fully electric, while the combustion engine can be used for longer distances.

A Smart Grid is an electricity grid equipped with modern computer systems and communication networks. The primary goal of a Smart Grid is controlling the distribution of electricity as optimal as possible. The advantages of using a Smart Grid are energy savings, cost reductions and greater reliability of the electric grid. Evidently, IT (information technology) will play a crucial role in coordinating the different actors in a Smart Grid [2, 3].

One particular interesting possibility in a Smart Grid is influencing the energy consumed by end users (DSM, demand side management). The main problem in consumption patterns is large peak demands which are typically balanced by production units with a high degree of pollution (e.g. coal plant) and can cause the net infrastructure to degrade or even lead to a black-out.

Because the impact of PHEVs on the electricity infrastructure will be significant [4], demand side management of PHEVs is an important research topic. The proposed DSM solution in this paper is a multi-agent (MAS) solution. MAS has been identified by the IEEE Power Engineering Society's Multi-Agent Systems (MAS) Working Group as a promising control approach in power engineering. The working group identified the key benefits MAS can bring about:

- *Flexibility*: the ability to respond to dynamic situations.
- *Extensibility*: the ability to easily add new functionality and augmenting or upgrading existing functionality.
- *Fault tolerance*: the ability of the system to meet its design objectives in case of failure.

The MAS solution for demand side management of PHEVs will be explained in three steps:

1. Assessment and quantification of the problem of increased peak demand caused by PHEVs in a distribution grid scenario. (section 2)
2. Description of a scheduler based on quadratic programming as optimal reference solution for DSM of PHEVs and the motivation why this solution is infeasible in practice. (section 3)
3. Description of an adaptable and scalable multi-agent system solution for DSM of PHEVs and comparison with the QP scheduler solution. (section 4)

Each of these steps is interlaced with simulation results. The last two sections discuss related work and conclusions.

2. INCREASED PEAK DEMAND CAUSED BY PHEVS

As a consequence of the increasing number of PHEVs, electricity demand is expected to rise significantly in the next decades. Because most PHEVs are expected to be charged after working hours, the existing peak demand in the evening will increase. To assess the gravity of this problem, a scenario of the distribution grid in 2030 is assembled and simulated on a desktop pc¹.

2.1 Realistic scenario of a distribution grid

To assess the peak demand problem, the scenario of a distribution grid on a scale of a city in Belgium (e.g Leuven) is assembled. The structure and capacity of a representative distribution grid in 2009 are obtained from the Belgian electricity provider Nuon [5]. A schematic description of this structure is depicted in figure 1. The actual scenario contains 59,250 households and 10,950 SMEs (small and medium enterprises). Research predicts that around 30% of the cars in Belgium will be PHEVs in 2030 [6]. Consequently, there are 17,775 PHEVs in the described scenario.

The consumption of households and SMEs is based on synthetic load profiles [7]. These profiles contain the average household consumption for every day of the year on a 15 minute base. These profiles provide a good estimate of the aggregated consumption at each transformer.

For a true representation of the load caused by PHEVs, a realistic model of PHEV usage is utilized [8]. This model represents the state of a car (home, driving, work, other) on a per minute base. Furthermore, to represent the average PHEV in 2030, the modern Chevrolet Volt is chosen, a PHEV that is expected to go in production at the end of 2010.

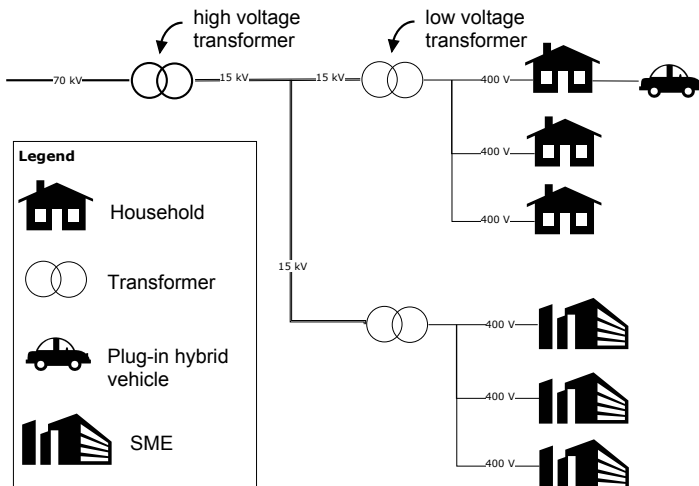


Figure 1: Schematic description of the structure of a distribution grid.

2.2 Simulation of the scenario

We have built a multi-agent simulator [9] to simulate the described distribution grid scenario. The behavior of the agents controlling the PHEVs in this scenario represents the expected behavior without demand side management;

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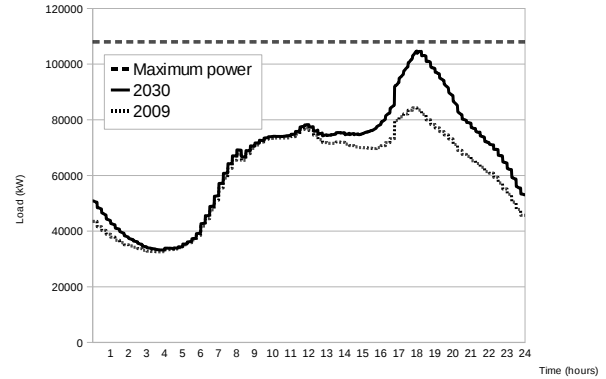


Figure 2: Current (2009) and simulated (2030) load of the high-voltage transformer on November 26.

if a PHEV is home, the PHEV is connected to the grid and charged until its battery is full. In figure 2, the current (2009) and simulated load (2030) of the high voltage transformer is shown for 26th of November (household consumption is assumed constant). The transformer is almost overloaded which can have serious consequences. The simulated peak load (2030) is around 20% higher than the current peak load (2009). Low voltage transformers show similar load patterns.

Results also indicate that the problem is much more serious in the winter season, because the peak load caused by households can be as much as 40 percent higher. Furthermore, the simulations indicated that the low voltage transformers get overloaded sooner than high voltage transformers. Nevertheless, the possible consequences of overloading a high voltage transformer are much higher.

The final goal of charging PHEVs is driving as much electrical as possible. In the described scenario, PHEVs are able to drive 70% of the time electrical and 30% of the time with combustion engine. Even with intelligent control, more electrical driving cannot be gained, because in this scenario, PHEVs charge at their maximum power. Consequently, these results will be used as a reference to evaluate optimal charging in the QP scheduler solution (section 3) and the MAS solution (section 4).

3. QP SCHEDULING FOR DEMAND SIDE MANAGEMENT OF PHEVS

In this section, an optimal scheduler is proposed as reference solution for demand side management of PHEVs. To optimally schedule the charging of PHEVs, all PHEVs have to send their future behavior (PHEV departure times, PHEV arrival times, drive times) on a daily basis to a scheduler at a central location (figure 3). After the central scheduler has determined a charging plan for each PHEV, these plans are sent back to the PHEVs.

Several scheduling techniques exist that are applied in domains like train operation [10] and production planning [11]. In this paper is chosen for quadratic programming (QP) as scheduling technique. QP is a technique for optimizing a quadratic function of several variables subject to linear constraints. In the rest of this section, the problem of DSM of PHEVs is translated to quadratic programming.

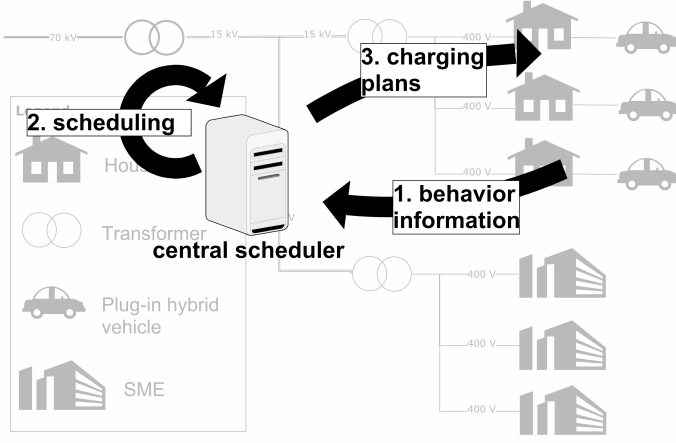


Figure 3: Central QP scheduler for demand side management of PHEVs

3.1 QP: Variables and domain

The variables that have to be optimized are the charging power of each vehicle at each point in time. In table 1, these variables (P_{xy}) are shown for M vehicles and N points of time. The total amount of variables is M·N.

The domain of the variables is defined between 0 kW and P_{max} kW, the maximum power possible at a regular household connection. If a PHEV is not at home, the maximum power is set to 0 to disallow charging.

	t_1	t_2	t_3	t_4	...	t_N
PHEV 1	P_{11}	P_{12}	P_{13}	P_{14}	...	P_{1N}
PHEV 2	P_{21}	P_{22}	P_{23}	P_{24}	...	P_{2N}
...
PHEV M	P_{M1}	P_{M2}	P_{M3}	P_{M4}	...	P_{MN}

Table 1: Variables

3.2 QP: Constraints

In addition to the power limitations of the household connection (defined by the domain), the battery of the PHEV also puts limitations on the power variables:

- The battery of a PHEV has to be charged enough to assure maximum electric driving.
- The battery of a PHEV cannot be charged beyond the maximum capacity of the battery.

Without taking into account these limitation, a wrong solution could be found. In that case for example, not charging the PHEVs could also be a possible solution to flatten the load.

The battery limitations are defined as constraints where every variable P_{xy} has an upper and lower bound, $P_{xy,min} \leq P_{xy} \leq P_{xy,max}$. In table 2, these bounds are shown for the first PHEV. Every bound is dependent on the charging power in the previous time steps. For example, if P_{11} was low, $P_{12,max}$ can be high, because the battery is still empty. The method developed for obtaining these bounds is omitted.

	P_{11}	P_{12}	P_{13}	...	P_{1N}
lower bound	$P_{11,min}$	$P_{12,min}$	$P_{13,min}$...	$P_{1N,min}$
upper bound	$P_{11,max}$	$P_{12,max}$	$P_{13,max}$...	$P_{1N,max}$

Table 2: Constraints for PHEV1

3.3 QP: Quadratic function

The optimal solution can be defined as the solution where the load at each transformer of a distribution net is flattened. In this reference solution, we limited scheduling to flattening the load only at the high voltage transformer. However, this will not affect the evaluation of the scheduler which leads up to using a multi-agent system. In table 3, the total load of the HV transformer at each time point (T_{toty}) is calculated by summing up the power of each PHEV (P_{xy}) and the total load of the households (H_{toty}) at each time point.

$$\begin{array}{cccccc}
P_{11} & P_{12} & P_{13} & P_{14} & \dots & P_{1N} \\
P_{21} & P_{22} & P_{23} & P_{24} & \dots & P_{2N} \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
P_{M1} & P_{M2} & P_{M3} & P_{M4} & \dots & P_{MN} \\
+ & H_{tot1} & H_{tot2} & H_{tot3} & H_{tot4} & \dots & H_{totN} \\
\hline
T_{tot1} & T_{tot2} & T_{tot3} & T_{tot4} & \dots & T_{totN}
\end{array}$$

Table 3: Total load at each time point

The variation between these loads has to be minimized to assure a flat load curve. A well-known measure in statistics to evaluate the variation of a set of variables is the variance:

$$VAR(P_{tot}) = \frac{\sum_{i=0}^N (T_{toti} - \mu)^2}{N}$$

By choosing the variance of the total load as quadratic function to minimize, QP can find the optimal solution.

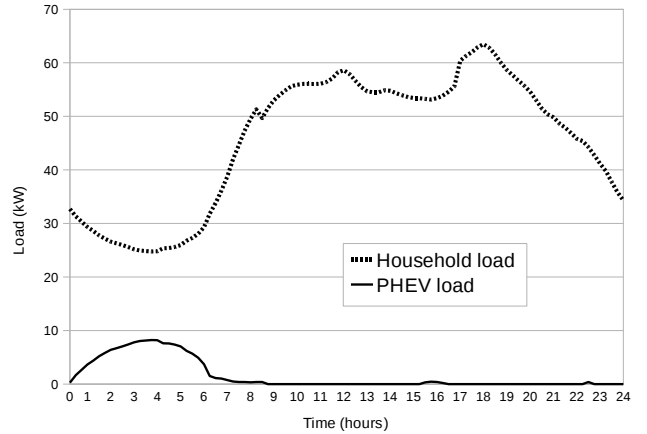


Figure 4: QP scheduling result of 50 PHEVs onto a household load.

3.4 Evaluation

For quadratic programming, the optimization package CPLEX [12] was used. In figure 4, the result of scheduling 50 PHEVs onto the household load is shown. The variance of this optimal solution is minimal. Because all constraints were respected,

PHEVs were able to gain maximal electric driving. Nevertheless, a central scheduler is infeasible because of a few important characteristics discussed in the following paragraphs.

Incomplete information The central scheduler is able to find an optimal solution, but this solution is strictly dependent on exact data about the behavior of PHEVs. In reality, exact data is not available. For example, it is impossible to know in advance the exact time when a PHEV connects to the electric grid.

Scalability Although the problem is convex and therefore solvable in polynomial time, the execution time is long due to the large number of variables. On our desktop pc, the execution time for scheduling 50 cars was several hours. In figure 5, the execution time on our desktop pc is depicted for an increasing amount of PHEVs. The increase is not exponential, but nonetheless very steep.

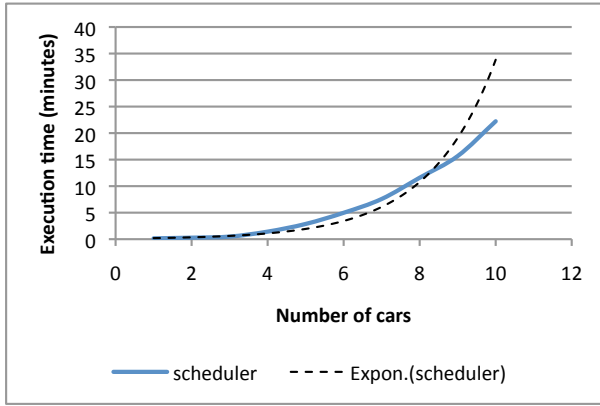


Figure 5: Execution time of a central scheduler for an increasing amount of PHEVs

Several techniques exist to design a scheduler. In this paper, quadratic programming was used to find an optimal reference solution. However, the need for complete information and poor scalability in terms of execution time make this solution unfeasible in practice.

4. A MULTI-AGENT SYSTEM FOR DEMAND SIDE MANAGEMENT OF PHEVS

Based on the identified limitations of a QP scheduler and the large-scale requirements of demand side management, a decentralized MAS approach is proposed. First, a schematic overview of the MAS is discussed where agents provide a way of flattening the load at each transformer. Hereafter, the coordination mechanism used by the agents to adapt to unpredictable behavior of PHEVs is explained. Finally, the proposed MAS is compared with the central scheduler.

4.1 Multi-agent system overview

The schematic overview of the multi-agent system is depicted in figure 6. A PHEV agent represents the software controlling a PHEV and a transformer agent controls a transformer. The goal of both type of agents:

- PHEV agent: *charge the battery of its PHEV in time.*

- Transformer agent: *flatten the load of its transformer and prevent overloading.*

These goals are not independent from each other. For example, a PHEV with an empty battery cannot be charged in an hour, because this would cause overloading the low voltage transformer. To meet the goals of all agents, the agents have to coordinate with each other through communication.

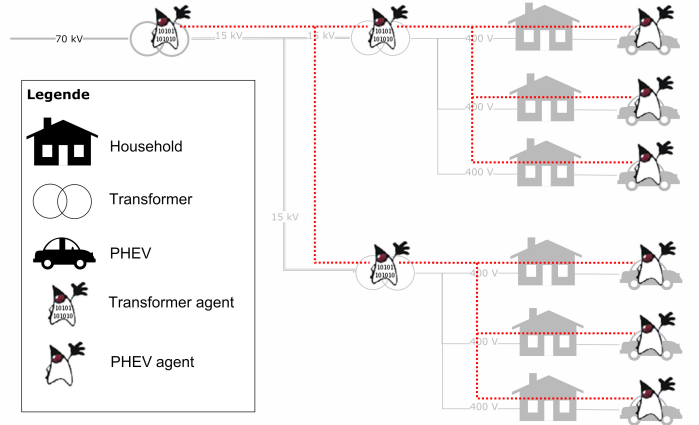


Figure 6: Schematic overview of the multi-agent system.

4.2 Coordination in a MAS for demand side management of PHEVs.

The basic coordination mechanism in the MAS consists of a PHEV agent requesting its permitted charge power to the transformer agents in the same branch of the distribution net. This mechanism contains 4 steps (figure 8):

1. PHEV agent sends its intentions to the connecting transformer agents.
2. The transformer agents individually determine the charge power that flattens the load at their transformer best.
3. The transformer agents negotiate with each other for a mutual charging power that flattens load best at both transformers.
4. The transformer agent at the low voltage transformer announces the mutual agreed charge power to the PHEV agent

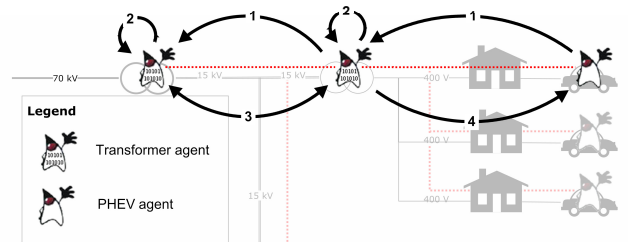


Figure 8: The coordination mechanism used by the agents.

The PHEV agents asynchronously send charge requests to the transformer agents at regular time intervals to keep the

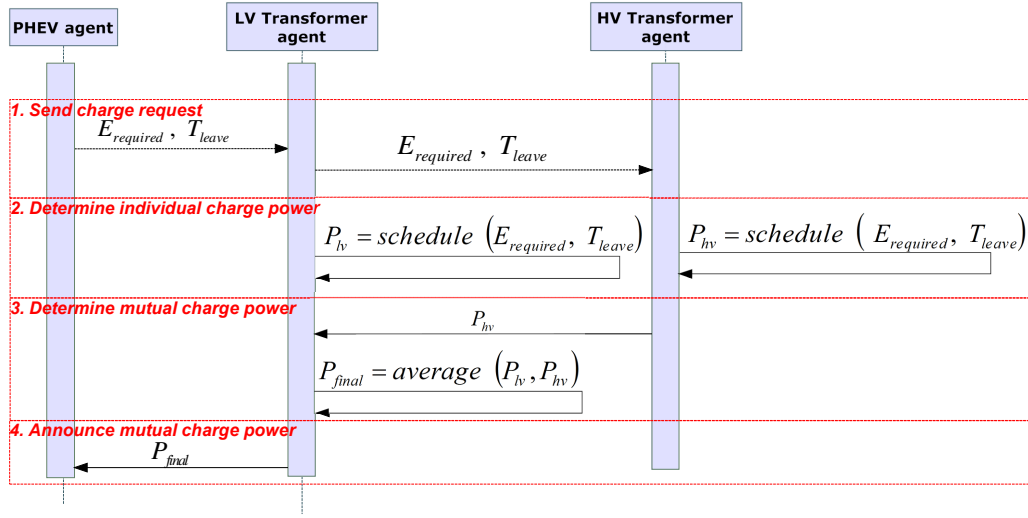


Figure 7: Energy limiter: interaction diagram

transformers informed of their intentions. Based on this coordination mechanism, two specific coordination strategies were developed: the energy limiter and the power limiter. In the energy limiter, an amount of energy is requested by the PHEV agents and in the power limiter, an amount of power is requested by the PHEV agents.

4.2.1 Energy limiter

The energy limiter is a coordination strategy where PHEVs reserve an amount of energy when they connect to the power grid. This mechanism requires some forecast data; transformer agents need forecasts about the household loads behind their transformer and PHEV agents need data about the battery level required by their PHEV and the expected departure time. These latter values can be estimated by data mining techniques, while the household load can be forecasted through analysis of historic data [7].

Figure 7 shows how a PHEV agent requests its charge power :

Step 1: A request for charging is sent from the PHEV to its connected LV transformer agent which forwards the request to the HV transformer agent. This request contains the required energy $E_{required}$ and the expected departure time T_{leave} .

Step 2: The LV transformer agent and the HV transformer agent reserve the requested energy at their transformer and determine the charge power of the requesting PHEV (see next paragraph, “Energy reservation” for details on the reservation system).

Step 3: The HV transformer agent sends its preferred PHEV charge power to the LV transformer agent. Then, the LV transformer agent calculates the average of the charging power determined by itself and the HV transformer agent to flatten the load at both transformers.

Step 4: The allowed charging power is sent back to the respective PHEV agent and the PHEV agent can adapt its charging power accordingly.

The PHEV agents have to resend requests at regular time intervals to confirm their energy reservations. If an energy

reservation is not confirmed, the transformers will delete the reservation after an expiration time. This way, the agents adapt dynamically to unexpected behavior of the PHEVs.

ENERGY RESERVATION. Reservation of energy is different from scheduling (section 3), because the arrival times of a PHEV are not known beforehand. Therefore, PHEVs can only reserve energy for charging their battery at the moment they arrive and connect to the grid. A small example clarifies how optimal reservations are obtained.

In this example, two PHEVs have sent a request for charging. PHEV1 has sent a request for 4 kWh in 1 hour, while PHEV2 has sent a request for 6 kWh in 4 hours. In figure 9, the load is shown if PHEV1 is reserved before PHEV2 and in figure 9b, the load is shown if PHEV2 is scheduled before PHEV1. Clearly, situation B is optimal because the total load is flattest. The general rule for optimally flattening the load is reserving the most constraint PHEVs first (the PHEVs that have the least time to charge their battery).

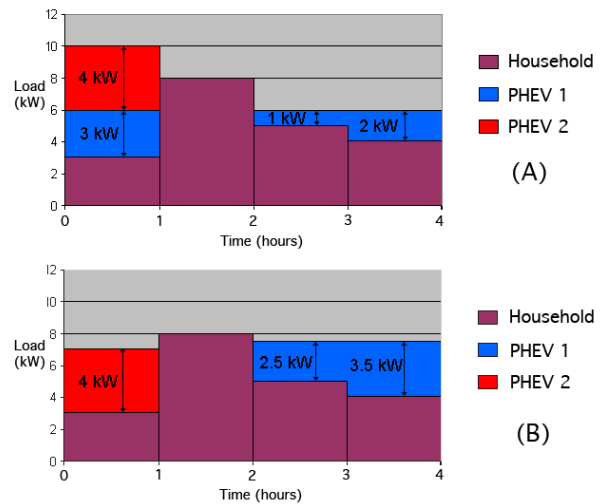


Figure 9: Optimal energy reservation.

4.2.2 Power limiter

The power limiter is a coordination mechanism where the load of PHEVs is flattened by using a low pass filter. The advantage of this mechanism is that no forecasts are required. Transformer agents only have to be able to measure the instantaneous load behind their transformer, while PHEV agents only need knowledge about the instantaneous battery content of their PHEV.

Figure 10 shows how a PHEV agent requests permission to charge its battery in the power limiter mechanism.

Step 1 A request for charging is sent from the PHEV to its connected LV transformer agent and forwarded to the HV transformer agent. This request contains the maximum power (P_{max}) permitted by a household connection.

Step 2 The transformer agents calculate the worst load possible by summing up the measured household load and the charge power requested from the n PHEVs that have a request pending:

$$P_{worst} = P_{households} + \sum_{i=0}^n P_{max}^n$$

P_{worst} is the load in the worst case scenario where the PHEVs are not controlled (figure 2). By filtering this power, the preferred load can be calculated:

$$P_{preferred} = \text{filter}(P_{worst})$$

The low pass filter actually limits the gradient of the load behind its transformer. This way, peaks and valleys in the load are smoothed out. The permitted load per vehicle can now be calculated by subtracting the household load from the preferred load and dividing by the number of vehicles:

$$P_{phev} = \frac{(P_{preferred} - P_{households})}{n}$$

If $P_{households} \geq P_{preferred}$, PHEVs are not allowed to charge their battery.

Step 3 The HV transformer agent sends its preferred charging power ($P_{phev,hv}$) to the LV transformer agent. Then, the LV transformer agent calculates the average of both charging powers ($P_{phev,hv}$ and $P_{phev,lv}$) to flatten the load at both transformers.

Step 4 The allowed charging power is sent back to the respective PHEV agent and the PHEV agent can start charging their battery.

The power limiter is a suitable solution in case no information about future load is known. By limiting the gradient of the load by a low pass filter, a more smooth profile is achieved. However, a drawback is the cut-off frequency of the low-pass filter that has to be determined beforehand. If this frequency is too high, peak loads will not be avoided. If this frequency is too low, PHEVs will not be charged enough.

4.3 Evaluation

The evaluation of the MAS solution is divided in the following criteria:

1. Optimality
How optimal is the MAS solution compared to the scheduling solution?

²In our simulations, a digital biquad filter [13] was used.

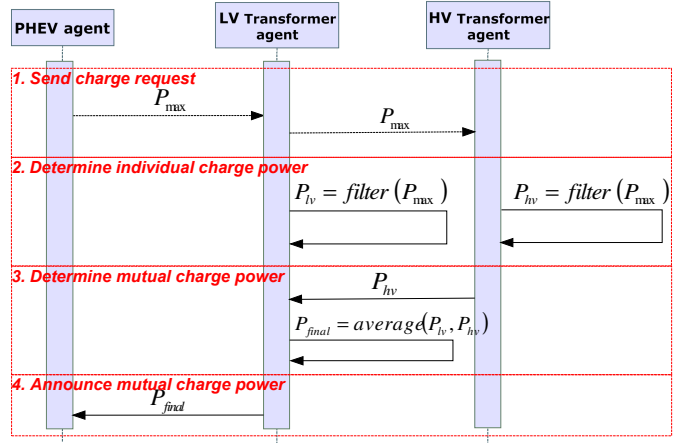


Figure 10: Power limiter: interaction diagram

2. Adaptability
How well can the MAS solution adapt to changing situations?
3. Scalability
How does the MAS solution scale with an increasing number of PHEVs?

In the next sections, every criteria is researched in detail.

4.3.1 Optimality

The two coordination mechanisms were tested in a simulation of the scenario described in section 2.1. The obtained load of the high voltage transformer is presented in figure 11. The low voltage transformers showed a similar load pattern. In terms of the variance, these profiles are 80-87% (power limiter) and 95% (energy limiter) optimal compared to the scheduler solution. The electric driving time was optimal in the energy limiter, while the electric driving time in the power limiter was strongly dependent on the cut-off frequency of the low pass filter (62-67% instead of an optimal 70%). A substantial improvement can be made by giving PHEVs with a lower battery level a higher priority.

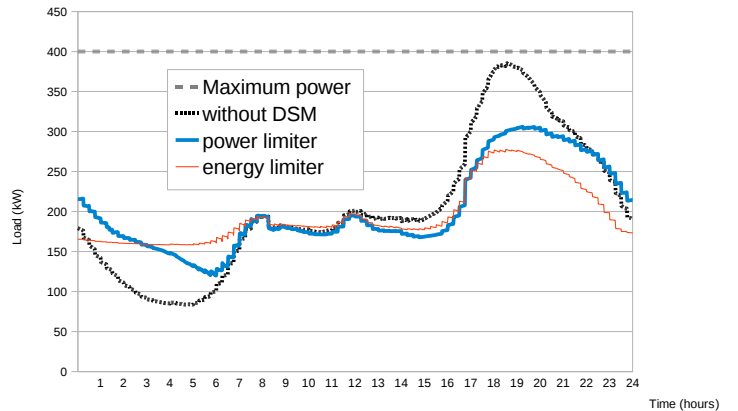


Figure 11: Load of different coordination strategies compared at a 400 kVA transformer.

4.3.2 adaptability

In contrary to the central scheduler, the MAS does not need exact data. Because the PHEV agents send their requests at regular time intervals, the transformer agents dynamically adapt their information about the expected load. For example, when a PHEV leaves, no request is sent any more and pending reservations at transformer agents will be deleted.

The adaptability of the MAS is determined by the rate at which requests of PHEV agents can be processed by the transformer agents. If a request is sent for the first time by a PHEV agent, the transformer agents have to reschedule. If a request from a PHEV contains the same intentions as the last request, no rescheduling is needed.

In the worst case (around 18.00h in the evening), 1000 cars connect in 5 minutes (figure 12). Simulations show that the energy limiter is able to reschedule 1371 requests in 5 minutes, while the power limiter is able to process around 32 million requests per minute. Both coordination strategies respond fast enough to assure an adaptable system.

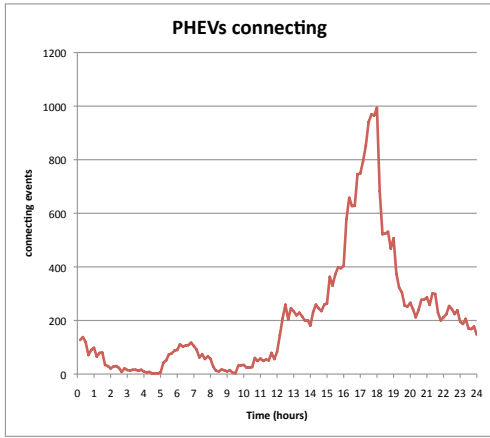


Figure 12: Number of PHEVs connecting per 5 minutes.

4.3.3 Scalability

In figure 13, the execution time of the energy limiter and the central scheduler is depicted for an increasing amount of PHEVs. The empirical tests show that the execution time increases closer to a linear curve than the central scheduler, which indicates better scalability.

The scalability of the power limiter is irrelevant, because the power limiter is extremely fast in processing requests.

5. RELATED WORK

In several research studies, multi-agent systems have been identified as the key technology in the future Smart Grid. Examples of MAS application in Smart Grids are island-mode control [14], micro-storage management [15] and micro grids [16].

Shao et al. [17] evaluates the impact of charging PHEVs on a residential scenario of 5 homes and concludes that on-peak charging causes the existing peak load to increase, while off-peak charging creates additional peak loads. Therefore, two charging strategies are proposed by Shao et al. The first strategy is stagger charge, where the transformer load is lim-

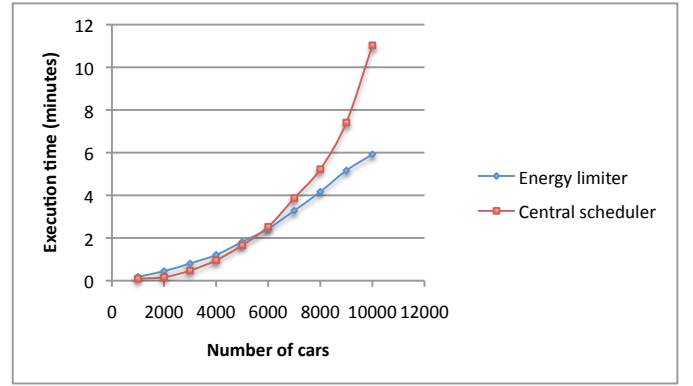


Figure 13: Execution time of the energy limiter for an increasing amount of PHEVs.

ited by a pre-defined value. Simulation results of this strategy indicate a peak load reduction, but some PHEVs cannot be charged in time. To account for this problem, the second strategy is a household load control strategy wherein non-critical household loads are shed or deferred when PHEVs are charging.

The MAS solution proposed in this paper provided solutions for demand side management of PHEVs where PHEVs are charged in time without shedding or deferring household loads. Furthermore, this paper addressed a scenario on scale of a medium-sized city in Belgium (e.g. Leuven) where load is considered at multiple transformers.

MAS has also been identified as a natural way of modeling market places in a Smart Grid [18, 19]. An important example is the Power Matcher in which agents buy (consumers) and sell (producers) on an electronic market. By determining the equilibrium price, demand and supply are matched. Currently, the PowerMatcher does not take into account network constraints which implies that peak loads and overloading of the infrastructure is still possible. Theoretical work on transport network feasible solutions for the PowerMatcher has been done [20], but at the moment this paper was written, not yet tested in simulations or field tests.

Li et al. [21] identified a distributed solution for supply and demand matching using stigmergy (via a common stigspace) in multi-agent systems. The resource agents (controlling a load or generator) in this system calculate plans for electricity demand or supply for a period in the future and send this plan to the stigspace. The broker agents constructs global goals using market and predicted usage data, e.g. a grid supply cap on the total power usage for a certain period of time. Depending on total demand and supply cap, the resource agents revise their plan until all goals are satisfied.

6. CONCLUSION AND FUTURE WORK

In the future, demand side management of PHEVs will become necessary to prevent peak loads. To identify the best solution for DSM, different DSM techniques must be compared. In this paper, we proposed a multi-agent solution and compared the qualities of this solution with an optimal reference solution obtained by quadratic programming.

Central scheduling through quadratic programming can obtain an optimal way of charging PHEVs, but is unfeasible in practice. Not all data about PHEVs is available to

perfectly schedule PHEVs and a central scheduler is little scalable. In this paper, a multi-agent system solution was proposed which is able to dynamically adapt to PHEV behavior. Two different coordination strategies were developed that take into account less data than the central scheduler; the energy limiter only uses predictions about loads, while the power limiter doesn't use any forecast data. To compensate for using less information, the system constantly adapts to new information through coordination between the agents.

This paper was a first initiative in comparing demand side management solutions for PHEVs. Future work will consist of, but will not be limited to, the following aspects:

SCENARIOS. To more thoroughly evaluate solutions for DSM, more realistic scenarios need to be tested. The scenario considered in this paper does not necessarily hold for each region. For example, city regions will have different characteristics compared to rural regions. Furthermore, PHEVs can also be charged at work or use quick charging, which was also not considered in this paper.

SCHEDULER. In our research, scheduling was achieved by quadratic programming. However, more advanced scheduling techniques exist such as genetic algorithm schedulers and stochastic schedulers. These types of schedulers will need further research to determine their adaptability and scalability. Furthermore, a distributed or hierarchical scheduler should be designed which is able to flatten the load at each transformer.

SCALABILITY. The scalability of a system is not only determined by execution time, but also by communication. The multi-agent system discussed in this paper is still open for improvement in this matter, because the agent at high voltage level still has to process messages from all PHEVs. A possible improvement here is aggregating requests at the LV transformer agents and hereby keeping communication to a minimum.

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